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Statistical Study of SCM Simulations Using Continuous Forcing Data Derived From NWP Products With the ARM Data Constraints

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Introduction

Statistical study of Single Column Model (SCM) results has been recently advocated by the ARM cloud parameterization and modeling working group. This is partly due to the sensitivity nature of Single Column Models (SCMs) to uncertainties in the initial conditions and the specified large-scale forcing. In addition, given the limitation of SCM framework (e.g. the lack of effective internal feedback between the SCM and the specified forcing) and the inevitable error in the initial conditions and the large-scale forcing, it might not be realistic to expect that SCMs can correctly capture every individual synoptic event. Statistical studies can help smooth out those random errors related to uncertainties in the initial conditions and the specified large-scale forcing so that one can focus on those physically important systematic errors from SCM simulations. Noted that, for climate simulations, it is more important for a given physical parameterization to successfully simulate statistics right for the process that is being parameterized.

This study conducts a statistical study of SCM simulations by using the ARM recently developed continuous forcing data for the year 2000. The NCAR CCM3 SCM is used in this study. The long-term continuous forcing data were developed from the NOAA mesoscale model RUC (Rapid Update Cycle) analysis using the ARM objective variational analysis approach, in which the ARM surface and the top of the atmosphere (TOA) measurements at Southern Great Plains (SGP) site are used as the constraining data. Seasonal averaged simulation biases in temperature, moisture, and surface precipitation rates are analyzed. Performance of the SCM to simulate the ARM observed seasonal averaged diurnal variations of surface precipitation and outgoing longwave radiative flux (OLR) is also discussed.

Continuous forcing data

As illustrated in Fig.1, the RUC analyses are used in place of sondes and wind profilers to develop the continuous SCM forcing data by using the variational analysis approach (Zhang and Lin, 1997; Zhang et al. 2001) constrained with the observed surface and TOA fluxes collected at the ARM SGP site for the year 2000. In the approach, the atmospheric state variables from the RUC analyses are adjusted to balance the observed column budgets of mass, heat, moisture, and momentum, rather than the RUC model-produced budgets. Xie et al. (2003) gave a detailed discussion about this approach and the quality of the derived continuous forcing data. They showed that applying the ARM column constraints could significantly improve the quality of the derived forcing data from the

RUC analyses. The continue forcing data derived from the RUC analyses agree considerably well with the observed forcing, especially for the seasons not dominated by strong convective convection.

SCM Simulations

The NCAR CCM3 SCM (CCM3) and the SCM with a modified cumulus convection scheme (CCM3m, Xie and Zhang, 2000) are used in this study. In the SCM runs, the large-scale total temperature and moisture forcings are specified from the continuous forcing data and the surface forcing is calculated by the model surface parameterizations. A series of a 36-hour forecast run is launched every day to avoid serious drift of SCM simulations. A composite of 12-36 hour forecasts from the series of 36-hour runs is analyzed.

Figures 2-4, respectively, show the seasonal mean of temperature biases, moisture biases, and surface precipitation rates simulated by CCM3 and CCM3m with the continuous forcing data. The original model (CCM3) (red-dashed lines) performs quite well in the Spring (MAM), Fall (SON), and Winter (JF) seasons while it shows relatively larger warm/dry biases in the Summer (JJA) season (Figs. 2-3). Consistent with the large warm/dry biases, CCM3 dramatically overestimates the observed precipitation during the Summer (Fig. 4). Examination of detailed time series of the model-produced precipitation during the Summer season shows that CCM3 almost rains every day with its maximum during the daytime. This is consistent with the results produced from the SCM driven by the forcing derived from sondes and wind profilers during Intensive Operational Periods (IOPs) (e.g., Xie and Zhang, 2000). Using the IOP forcings, Xie and Zhang (2000) found that the overactive convection in CCM3 was mainly due to deficiencies in the triggering condition used in the CCM3 deep convection scheme. In the model, convection is triggered whenever there is positive convective available potential energy (CAPE), which happens to occur during daytime due to strong solar heating of the land surface during the Summer. The triggering problem is less serious in other seasons where the diurnal variation of CAPE is weak due to weak diurnal variations of surface fluxes. In fact, CCM3 can reproduce well the observed precipitation during the Winter season as well as during the early Spring and late Fall seasons found in this study (not shown). Using an improved convective triggering mechanism, which is based on the large-scale dynamical forcing (see Xie and Zhang (2000) for details), CCM3m (black lines) significantly reduces the problem shown in CCM3 during the Summer. CCM3m also shows moderate improvements in the simulated surface precipitation for other seasons (Fig. 4).

Figure 5 compares the observed and the model-produced diurnal cycle of surface precipitation rates in different seasons. The observed precipitation shows its maximum at mid-night during the Spring and Fall seasons and in early morning during the Summer. The diurnal variation is weak during the Winter. It is seen that the original model CCM3 exhibits much stronger diurnal cycle than the observed for the Spring, Fall, and Summer seasons. The maximum precipitation produced by the model is seen near 2 pm local time, which is consistent with the maximum CAPE generated during the day (not shown). In

contrast, this problem is greatly reduced with an improved triggering function (CCM3m). Both model typically capture well the observed diurnal cycle during the Winter.

The observed OLR shows very clear diurnal cycle with its maximum near 2 pm local time for all the seasons (Fig. 6). CCM3 shows similar diurnal cycle for the Spring, Summer, and Fall seasons as those observed, but it produces a rather weak diurnal cycle during the Winter. During the Summer, the model produces considerably less OLR than the observed. This might be related to the overactive convection generated by the model, which results in more deep convective clouds than the observed and thereby reducing the outgoing longwave radiation. During other seasons, the underestimation is reduced. It is noted that the model overestimates the observed OLR at night during the Winter and the Spring. CCM3m generally shows better agreement with the observation than CCM3 for all the seasons. The largest improvement is seen in the Summer.

Summary

This study has shown preliminary results of using the ARM recently developed one-year continuous forcing data for statistical study of SCM simulations. The NCAR CCM3 SCM is used in this study. It has been shown that the SCM performs quite well in the Spring, Fall, and Winter seasons while it shows large warm/dry biases in the Summer season. The large warm/dry biases are closely related to overactive convection in the model, where convection is triggered too often by the model cumulus convection scheme. A diurnal analysis of surface precipitation rates shows that the model exhibits much stronger diurnal cycle with the peak around 2 pm local time during the Spring, Summer, and Autumn seasons, compared to the observations where the peak precipitation usually occurs at night or in early morning. The SCM generally captures well the observed diurnal variation during the Spring, Summer, and Fall seasons, but it underestimates its magnitudes. It also fails to reproduce the observed diurnal cycle of OLR in the winter season. Noted that these problems are also presented in the SCM driven by the ARM IOP forcings in simulating detailed individual synoptic events. It is worthy emphasizing here that results from this statistical study indicate that these errors are systematically and climatically significant. Reducing deficiencies in associated parameterizations could result in an improvement of climate simulations. This study has shown that the statistics of SCM simulations can be considerably improved when an improved convection scheme is used.

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References

Xie, S.C., and M.H. Zhang, 2000: Impact of the convective triggering function on single-column model simulations. *J. Geophys. Research*, 105, 14983-14996.

Xie, S. C., R. T. Cederwall, M. Zhang, and J. Yio, 2003: Developing continuous SCM/CSRM forcing using NWP products constrained by ARM observations. *To be submitted to J. Geophys. Res.*

Zhang, M. H., and J. L. Lin, 1997: Constrained variational analysis of sounding data bases on column-integrated budgets of mass, heat, moisture, and momentum: Approach and application to ARM measurements. *J. Atmos. Sci.*, 54, 1503-1524.

Zhang, M. H., J. L. Lin, R. T. Cederwall, J. J. Yio, and S. C. Xie, 2001: Objective analysis of ARM IOP Data: Method and sensitivity. *Mon. Weather Rev.*, 129, 295-311.

Figure Captions

Figure 1. A diagram that illustrates the approach used to derive the long-term continuous forcing using the RUC analyses constrained by the ARM observations. Circles enclosed by dashed lines are for the data that are not available or not used in developing the continuous forcing data.

Figure 2. Seasonal mean of temperature biases produced by CCM3 and CCM3m.

Figure 3. Same as Figure 2 except for the moisture biases.

Figure 4. Seasonal mean observed and model-produced surface precipitation rates (mm day^{-1}).

Figure 5. Diurnal cycle of the observed and model-produced surface precipitation rates (mm day^{-1}).

Figure 6. Same as Figure 5 except for out-going longwave radiation (OLR) (W m^{-2}).

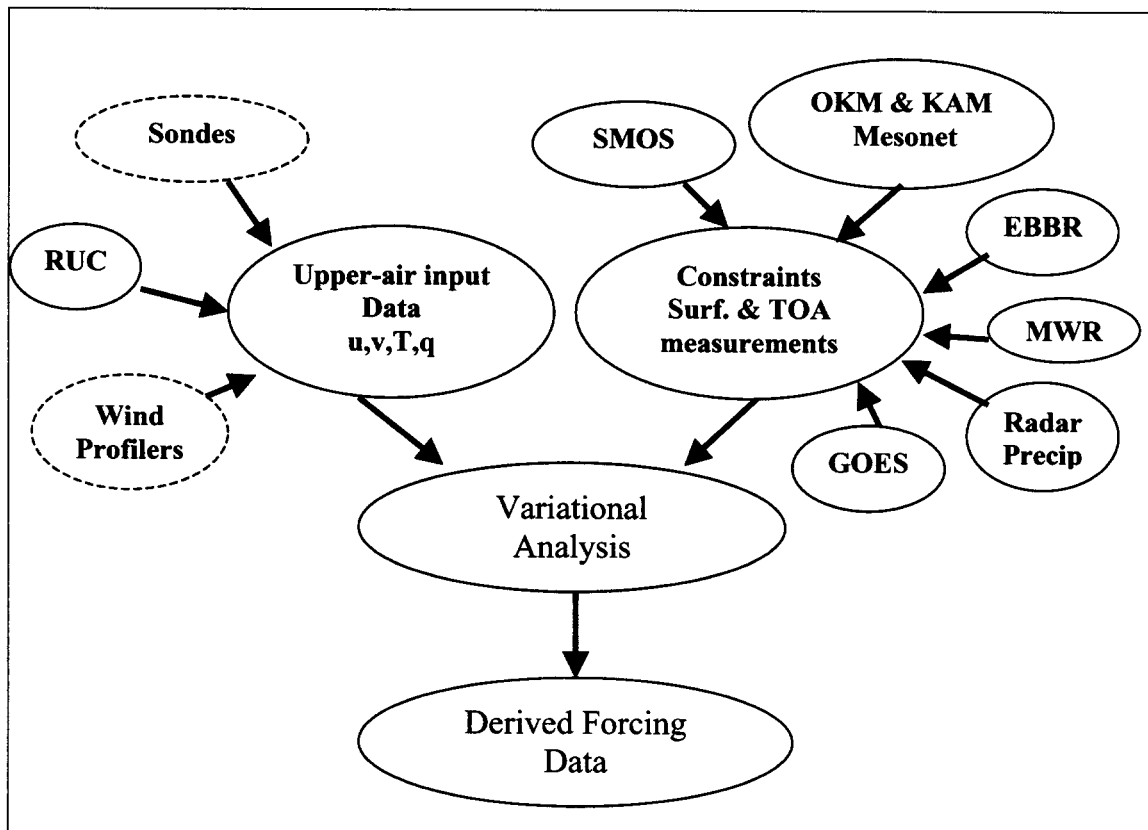


Figure 1

Seasonal Mean of T Errors

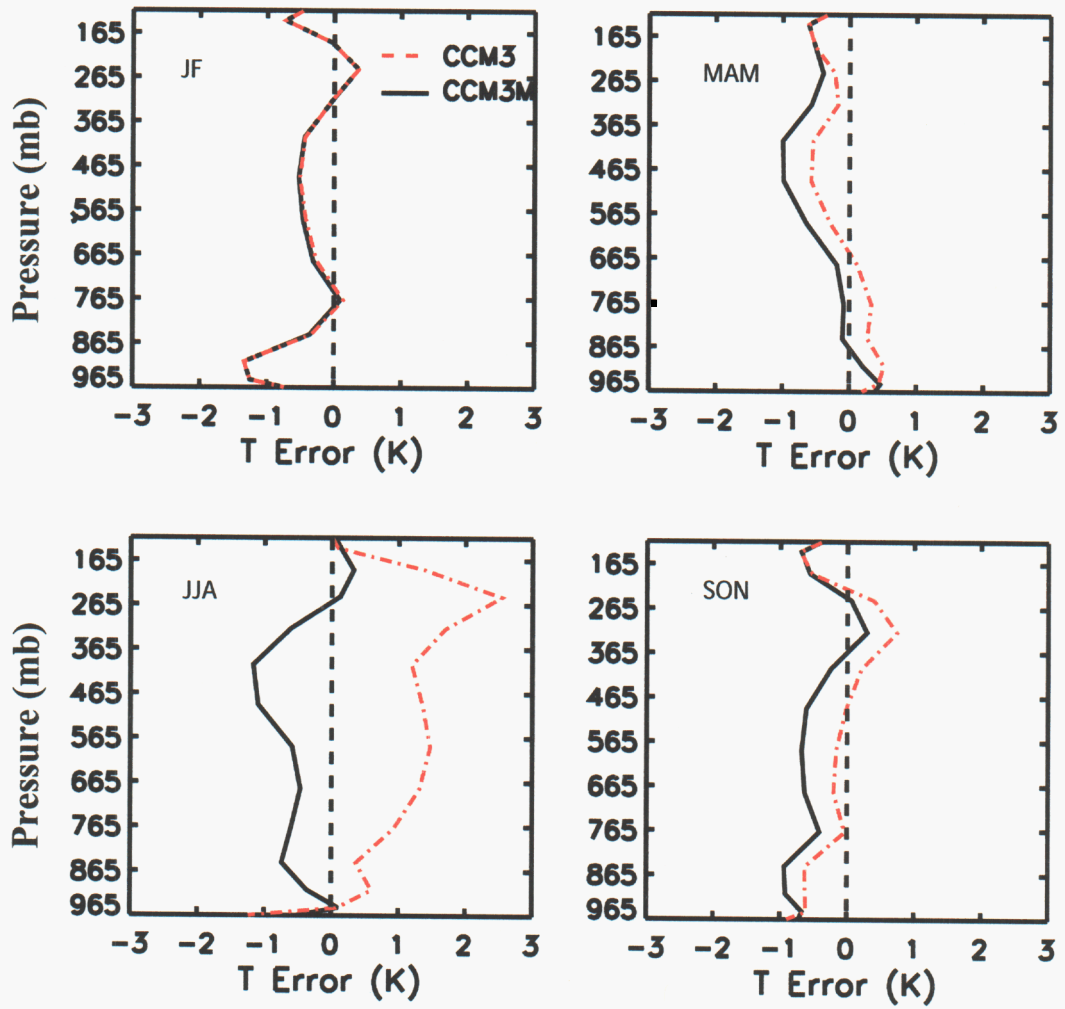


Figure 2

Seasonal Mean of q Errors

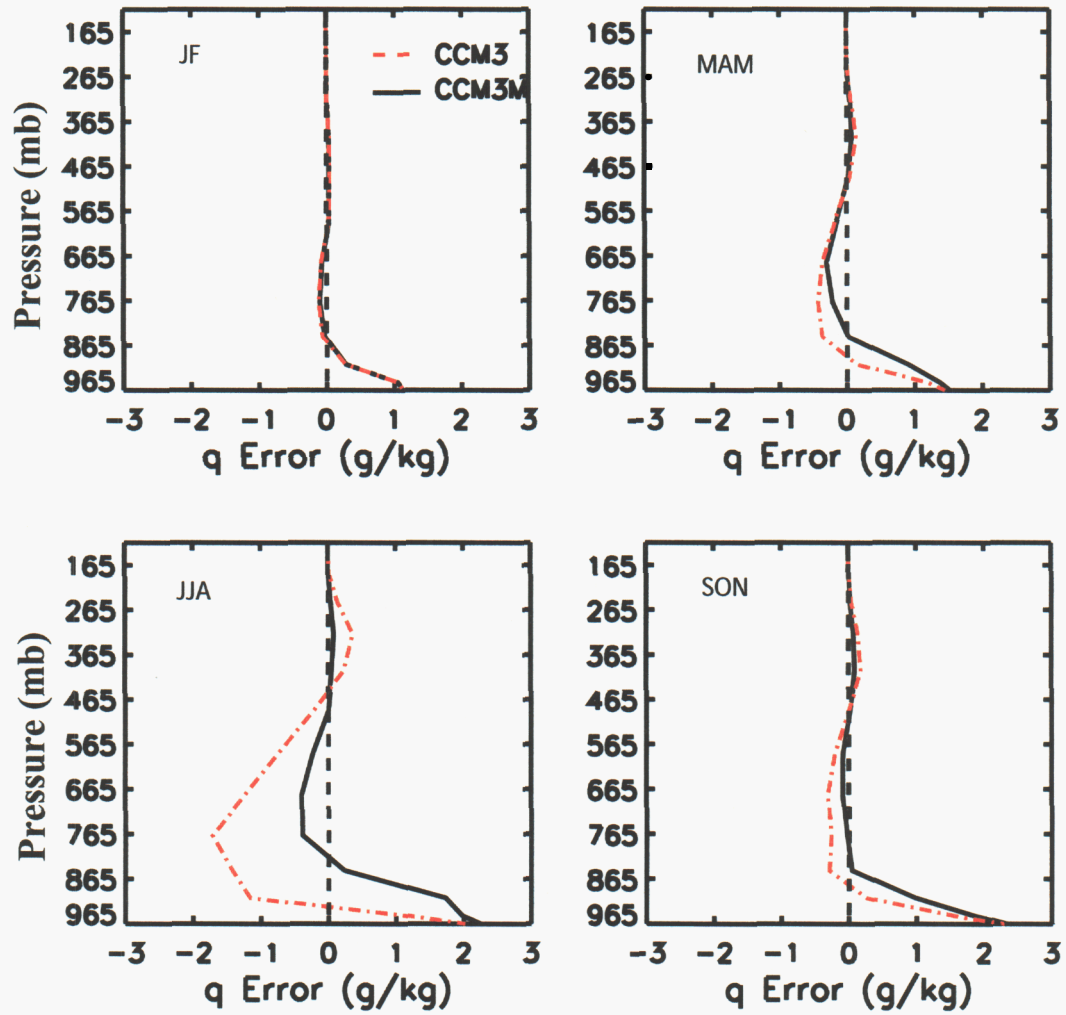


Figure 3

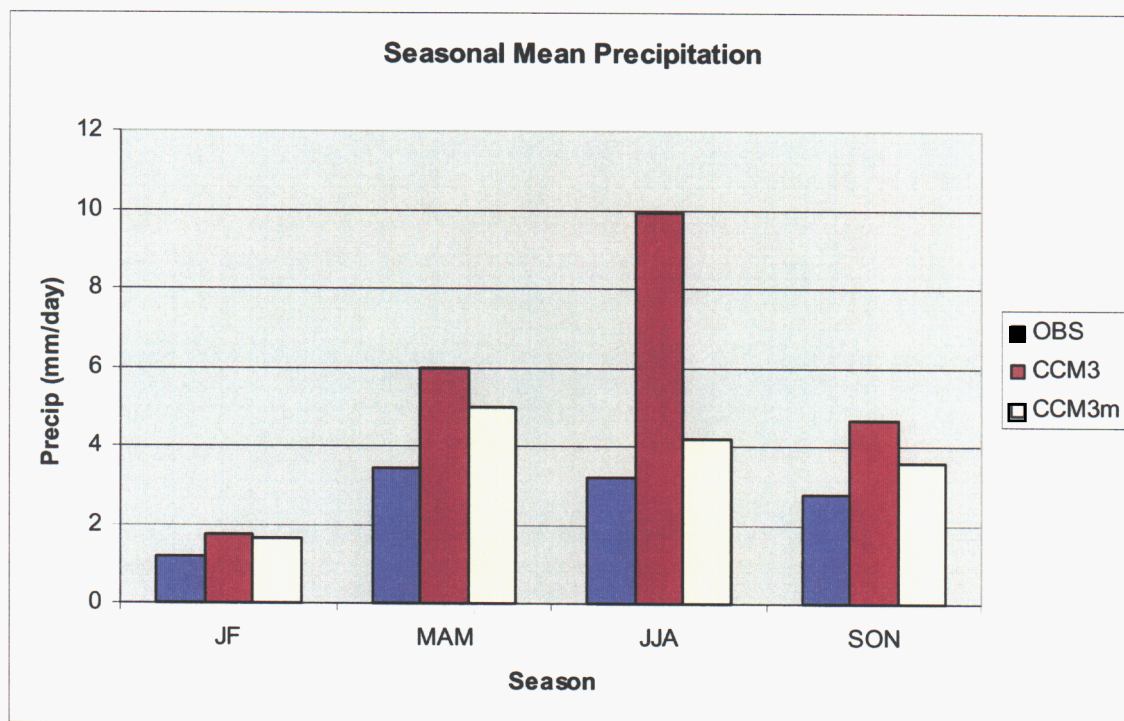


Figure 4

Diurnal Cycle of Surface Precipitation Rates

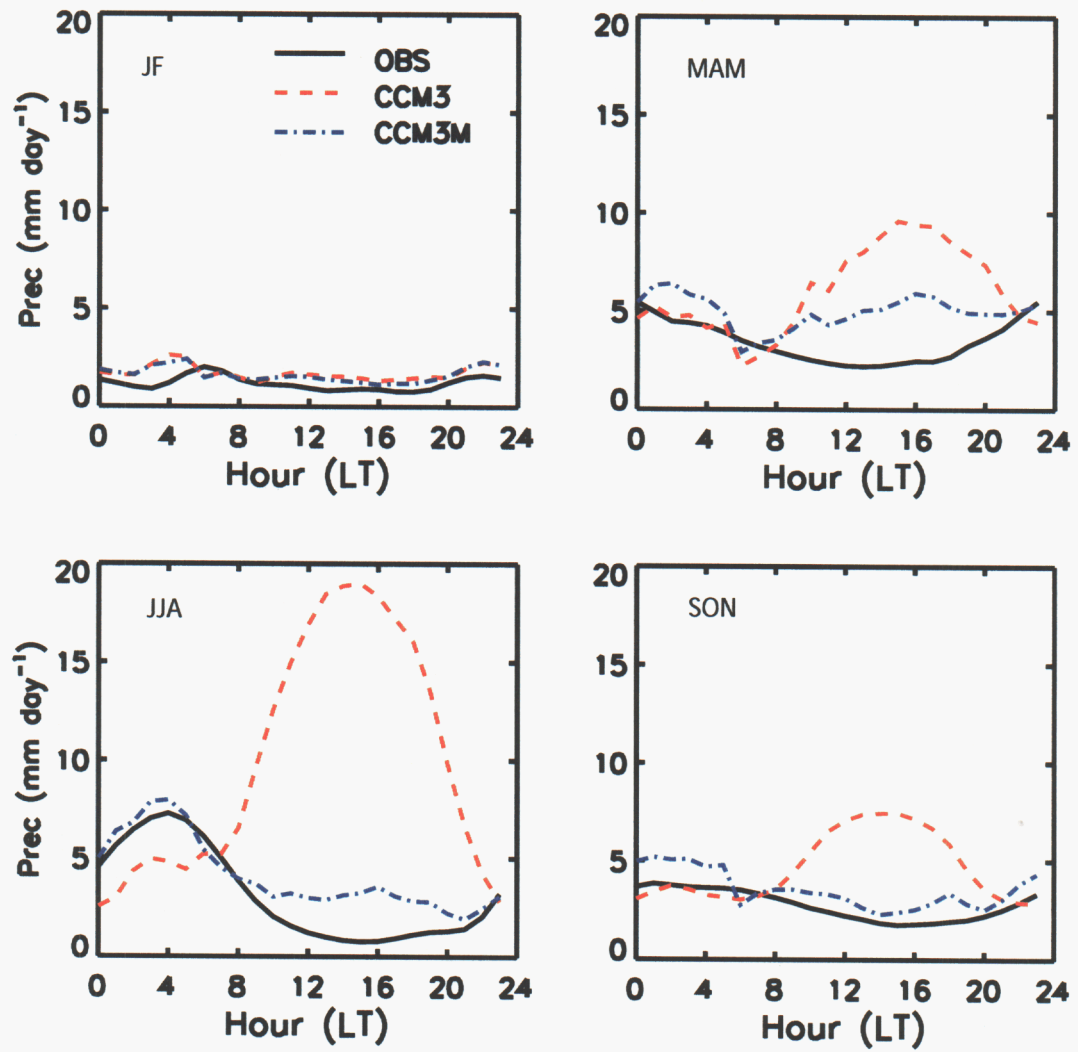


Figure 5

Diurnal Cycle of OLR

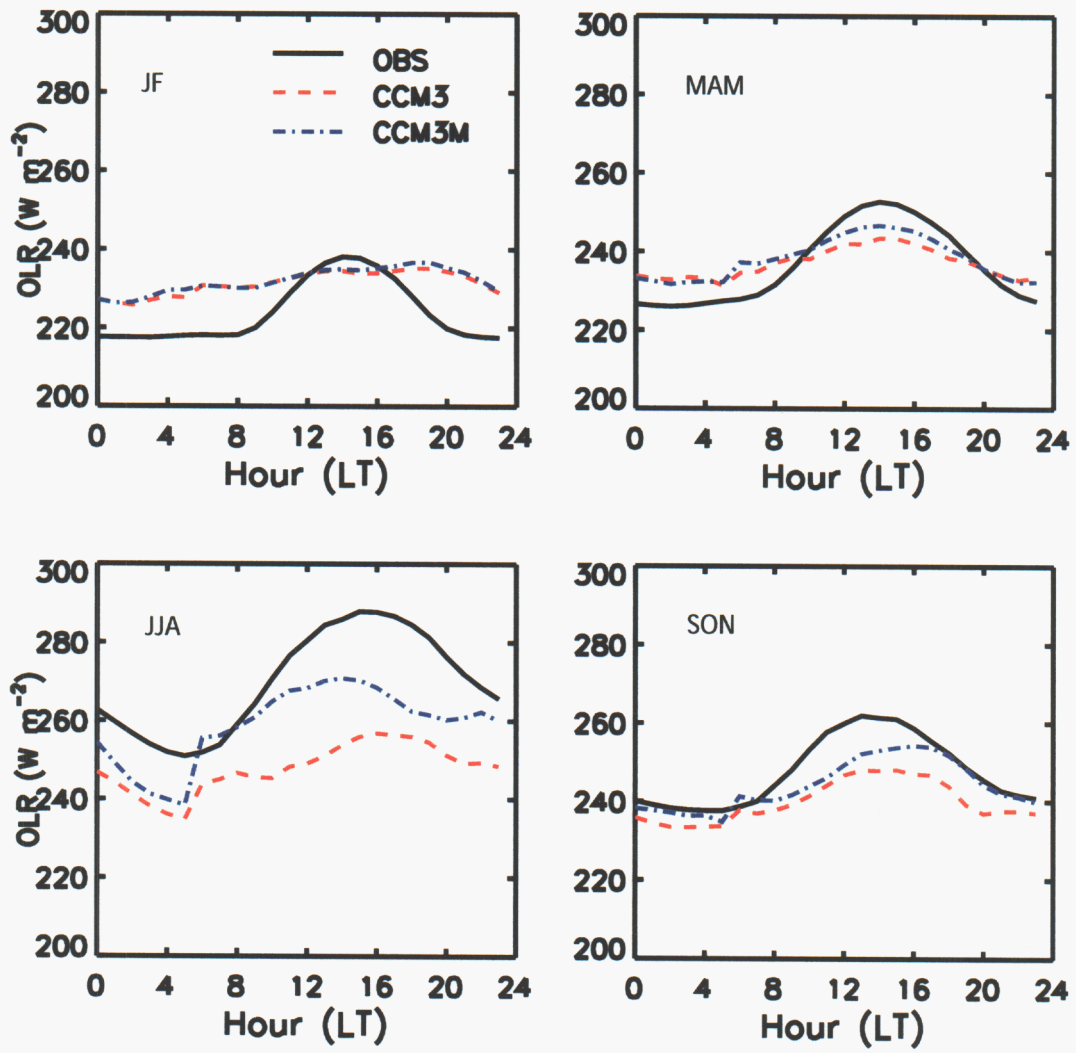


Figure 6